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ABSTRACT

A study was undertaken to develop a system for predicting the impact of adjustments in aptitude requirements on outcomes (performance) in Air Force basic resident technical training. To accomplish this, a multivariate modeling approach was used. Initially, interviews were constructed within a variety of technical training programs to specify the significant student input, course content, and training outcome variables. Measures of each of these variables were then formulated on the basis of documentary materials and standard Air Force appraisal indices. Subsequently, measures of these variables were obtained in 39 occupational specialties incorporating some 5,000 trainees. The relationships observed among these variables were used to develop a hypothetical model that was validated through a formal path analysis. The resulting model produced a residual of .19 and a highly interpretable pattern of path coefficients. When cross-validated on a sample of nine additional specialties containing 1,000 individuals, this model was found to predict observed training outcomes with less than one-third of a standard deviation in error. The implications of the model for understanding the Air Force technical training processes were then laid out along with some potential applications. (Four tables are appended.) (Author/YLB)

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Assessing the Validity of Air Force
Selection and Training Strategies

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Abstract

The present study was undertaken in an attempt to develop a system for predicting the impact of aptitude requirement adjustments on outcomes in Air Force basic resident technical training. To accomplish this a multivariate modeling approach was employed. Initially, interviews were constructed within a variety of technical training programs to specify the significant student input, course content and training outcome variables. Measures of each of the variables were then formulated on the basis of documentary materials and standard Air Force appraisal indices. Subsequently, measures of these variables were obtained in 39 occupational specialties incorporating some 5000 trainees. The relationships observed among these variables were employed to develop a hypothetical model that was validated through a formal path analysis. The resulting model produced a residual of .19, and a highly interpretable pattern of path coefficients. When cross validated on a sample of 9 additional specialties containing 1000 individuals, it was found that this model could predict observed training outcomes with less than 1/3 of a standard deviation in error. The implications of the model for understanding the Air Force technical training processes were then laid out along with some potential applications.

Introduction

It has long been recognized that job performance is one of the primary determinants of organizational effectiveness. While a number of approaches to the enhancement of individual performance might serve to increase organizational effectiveness, the appropriate allocation of individuals to jobs appears to be especially important (Schneider, 1977). In fact, Schmidt, Hunter, McKenzie and Muldrow (1979) have shown that a single organization may save itself millions of dollars each year simply by assigning to jobs only those individuals who possess an optimal combination of the attributes likely to facilitate task performance. Cognizance of these potential outcomes has led manpower allocation to become a major issue in military personnel management. This is especially true in the Air Force since each year tens of thousands of individuals must be assigned to and provided training in some 200 alternate technical specialties, and inappropriate assignments with respect to organizational needs may have a marked impact on mission readiness and training costs.

As a result of these considerations, the Air Force has attempted to formulate a reasonably cohesive paradigm for manpower allocation. As in any other manpower allocation system the Air Force relies on two central pieces of information: 1) a description of the performance relevant attributes possessed by the individual, and 2) a procedure for relating these attributes to performance in various jobs within constraints set by broader organizational needs. A number of descriptions of the individual are considered in the Air Force allocation system, including physical capacity,

expressed job preference, and aptitude among others. However, the primary description is obtained from the individual's scores on mechanical, administrative, general and electronic aptitude area composites derived from the Armed Services Vocational Aptitude Battery (ASVAB). The Air Force has traditionally employed a relatively straightforward strategy in using these ASVAB area scores in classification efforts. Essentially, it is argued that in a finite manpower pool the needs of the Air Force are best served by assigning the most talented individuals to the most demanding occupational specialties (AFSs). Operationally, this strategy has been implemented by establishing the validity of each composite for predicting performance in an AFS, and then setting varying minimums for entry into those specialties lying in each aptitude area on the basis of their relative difficulty.

Historically, the relative difficulty of Air Force specialties has been defined by training program attrition rates. In the sense that an individual's successful completion of basic resident technical training constitutes a minimum hurdle for entry into an AFS, the use of training performance as a basis for setting aptitude minimums may not be inappropriate. However, it must be recognized that attrition rates and training performance are influenced by a variety of factors aside from aptitude and occupational difficulty. When this observation was coupled with the fundamental importance of obtaining an adequate definition of occupational difficulty in the Air Force manpower allocation system, it led the Air Force Human Resources Laboratory (AFHRL) to attempt to develop a more direct and valid measure of the relative difficulty of Air Force occupational specialties. This work culminated in AFHRL's construction of the occupational

learning difficulty index. In accordance with Cronbach and Snow (1977) findings, this index assumes that given constant aptitude a more difficult task will take a longer time to learn. This suggested that a measure of occupational difficulty might be formulated by obtaining a weighted combination of subject matter experts evaluations of the time individuals require to master specialty tasks (Christal, 1976). Research along these lines has served to demonstrate the validity and feasibility of employing this index to define the relative difficulty of AFSs lying in a given aptitude area. Moreover, this research has indicated that, due to the existence of misalignments between existing aptitude minimums and the relative difficulty of AFSs, optimal manpower allocation is likely to require adjustments in some of the existing aptitude minimums.

Given the fundamental importance of the aptitude minimums in the Air Force manpower allocation system, it was felt that somewhat more detailed information should be obtained which would allow Air Force personnel managers to predict the likely impact of any aptitude requirement adjustments on performance in basic resident technical training. It was also hoped that a system could be developed which would also allow personnel managers to identify training strategies that might offset any negative changes in performance resulting from adjustment of aptitude minimums with respect to learning difficulty. The present investigation was undertaken in an attempt to meet these two goals.

At the outset of this investigation it was decided that a multivariate modeling methodology would provide the most appropriate vehicle for achieving

the foregoing goals. This decision was based on three considerations. First, it appeared that an adequate description of training performance could be obtained only by considering multiple outcome variables ranging from attrition rates to achievement test scores (Kirkpatric, 1959). Second, as Cronbach and Snow (1977) have pointed out, the effects of aptitude on training performance might be moderated by or expressed through a variety of other student input variables, such as reading ability or achievement motivation. Third, attributes of course content, such as abstract knowledge requirements or instructor quality, might serve to moderate the relationship between aptitude, occupational learning difficulty and training performance (Fox, Taylor & Caylor, 1967). While these considerations argued for a multivariate modeling effort, the need to apply this model in making routine predictions for some 200 AFSs lead to two constraints on the content and nature of the modeling effort since practical application seemed to call for the use of existing or readily available measures of all student input, cause content and training outcome variables as well as measures that could be applied in describing all AFSs.

Methods

Variables and Measures

The first step taken in this multivariate modeling effort entailed defining the major outcomes of basic resident technical training along with the student input and course content variables most likely to influence these outcomes. Additionally, at this time an attempt was to be made to identify potential measures of these variables, and obtain information concerning any

readily apparent biases on limitations in the general application of these measures. To obtain this information a series of structural group interviews were conducted at the Air Force's four major technical training centers during the winter of 1983. The various interview groups were chosen to provide a comprehensive description of the technical training process. The groups selected for these interviews included training wing commanders, branch chiefs, training managers, course supervisors, instructors, measurement section heads, instructional systems development section heads, and registrars. At each base, an attempt was made to target interview questions on the group's area of expertise as it pertained to the goals of the study. Table 1 presents the student input variables and course content variables which these subject matter experts believed had a significant impact on performance along with the relevant outcome variables. In all, 7 student input, 16 course content and 7 outcome variables are identified in these interviews that appeared to have some import across AFSs in describing the technical training process. The measures of these variables indicated by the interview results are also presented in Table 1 along with sources used to obtain this descriptive information.

While for the most part the information presented in Table 1 is self explanatory, there are certain major findings which should be elaborated before proceeding with the body of this discussion. First, measures of the vast majority of the variables signaled out by the interview groups were developed. However, a few variables mentioned in the interviews, such as resistance to stress and student equipment ratios, were eliminated here due to their lack of general significance across AFSs, or difficulties in

measurement. Second, the simple interest and preference interest constructs were only tentatively considered for inclusion in the present study due to the ambiguous nature of the choice data generated by recruits with a limited knowledge of AFS job requirements. Third, all outcome measures were obtained from the standard student evaluation record which was found to be a highly accurate and comprehensive record of training performance, such that the reasons for any special assistance were recorded on this form along with the time devoted to this effort. Fourth, in all cases the best available evidence indicated that the reliability of the student input, course content and training outcome measures lay at or above .80.

Sample

Having specified a reasonably comprehensive set of student input, course content and training outcome variables and measures of these variables, the next step in this modeling effort entailed obtaining a sample that would allow a general definition of the relationships among these constructs. The need to develop a general model as well as the need to cross validate this model led to the use of the following sampling paradigm. Initially, Air Force personnel administrators designated 40 AFSs, to be employed in model development. These specialties were chosen to ensure diversity in AFS content, coverage of all four aptitude areas, coverage of all major training centers, diversity in cost and diversity in yearly flow. Subsequently, 10 additional AFSs were designated on the basis of the foregoing criteria as a holdout sample for use in cross validation. Within each of these AFSs, a minimum of 50 individuals assigned to five different class groups were

designated for inclusion in the sample. Once the baseline sample had been obtained all other individuals entering the AFS between September 1983 and February 1984 were designated for inclusion in the study. It was hoped that the two fold sampling strategy would insure both a representative sample of AFSs and a representative sample of the recruit population.

Once the AFSs and subjects to be employed in the study had been designated, all documentary materials required to formulate measures of the content of training in each AFS were provided by training center officials as part of a site visit conducted during the summer of 1984. It is of note that these documentating materials were to be those describing the training program in the latter half of 1983. At the time of these site visits, copies of the student evaluation record were provided by the registrars office for all individuals included in the study sample. Subsequently, AFHRL employed existing data files to provide the information required for assessing student inputs. In coding this information it was assumed that the status of an AFS on the course content variable could be used to describe all individuals being trained in the AFS during this period.

The procedures sketched out above provided usable data for 39 of the AFSs designated for use in model development, and 9 of the AFS's designated for use in cross validation. In all, 5081 subjects were included in the model development sample and 889 subjects were included in the cross-validation sample. Examination of the samples demographic characteristics indicated that both the model development and cross-validation samples

displayed characteristics typical of Air Force recruit population as a whole. For instance, both samples were composed primarily of nonminority males who had completed high school and had an average age of 20. Further, no marked differences were observed between the demographic characteristics of the model development and cross validation samples that could not reasonably be attributed to differences in the content of the AFSs designated for study.

Procedures

Once the requisite sample had been obtained and measures of the relevant variables had been generated in the model development and cross validation samples, the following series of analyses were carried out. Initially, the mean and standard deviation of subjects scores on each of the student input, course content and training outcome variables were obtained within the total sample, the model development sample and the cross validation sample. Subsequently, this same information was obtained within each AFS designated for inclusion in the study at hand.

After these preliminary descriptive analyses had been completed subjects scores on the various student input, course content and training outcome variables were intercorrelated within the total sample, the model development sample and the cross-validation sample. The pattern of the correlation coefficients obtained in the model development sample was then reviewed and interpreted. When this empirical data was coupled with the descriptive information obtained in the interviews, it provided the background for construction of a hypothetical model interrelating the student input, course content and training outcome variables. Construction of this hypothetical

model was a highly complex process carried out in a series of discussions with knowledgeable Air Force personnel.

This hypothetical model provided the framework required for development of the formal multivariate model. The initial hypothetical model was used to generate the path specifications to be employed in a Lisrel V analysis of the correlations obtained in the model development sample. In carrying out this analysis it was held that the possibility of correlated error among the various measures should be considered. The goodness of fit test and residual term generated by the Lisrel V analysis was used to assess the extent to which the hypothetical model provided an adequate description of the relationships observed among the student input, course content and training outcome variables. The multiple Rs generated by the model against each of the endogenous, dependent variables were also obtained, along with the standardized path and regression coefficients generated by the Lisrel V program in optimizing fit between the hypothetical model and the observed correlation matrix. The regression and path coefficients generated in this analysis provided a basis for assessing the causal impact of the various student input and course content variables on training outcomes and formulating predictions of these outcomes given a knowledge of the AFS's status on the relevant student input and course content variables.

Once this empirical model had been formulated it seemed necessary to assess the accuracy, stability and generality of the predictions of training outcomes it provided. To accomplish this the standard scores of the 9 cross-validation AFSs on the student input and course content variables were

obtained. The regression equations generated by the model were then used to produce predicted scores on each outcome variables for each of the 9 AFSs. Subsequently, these predicted outcomes were compared to the outcomes actually obtained for each. In reviewing the results of this analysis, an attempt was made to identify any sources of systematic over and under prediction associated with AFS content in order to assess the feasibility of applying this model to make predictions for a number of AFSs lying in different career fields.

Results

Descriptive Findings

Table two presents the mean and standard deviation of scores on the student input, course content and training outcome variables in the total sample as well as the model development and cross-validation samples. Overall, this descriptive data is in line with the known characteristics of Air Force trainees and training programs. However, there are a few results that emerged in this analysis that are worthy of elaboration. As indexed by student inputs, such as selector AI scores, and course content variables, such as course length, it appeared that the cross validation sample was comprised of AFSs, associated with somewhat more demanding training programs. It was also found that yearly flow has an unusually high mean and standard deviation in the model development sample, apparently due to the inclusion of a few AFSs, such as security specialist, having an extremely high yearly flow. Table two also indicates that both academic and nonacademic attrition were relatively rare events. In fact, only 164 attritions were obtained in

the total sample, and only one nonacademic attrition was obtained in the cross validation sample. Finally, it appears that negative academic outcomes, such as academic counseling and academic attrition, occur substantially more frequently than negative nonacademic outcomes.

Inspection of the relationships among the student input, course content and training outcome variables produced a number of noteworthy findings. First, the two interest measures produced a weak pattern of relationships that proved difficult to interpret. Consequently, these measures were not considered in further analyses. Second, the remaining student input variables, such as aptitude and academic motivation, tended to display positive relationships on the order of .50. Third, these student input variables tended to produce correlations with achievement test grades lying between .20 and .35. Fourth, the student inputs were not significantly related to any of the more distal training outcomes, such as academic or nonacademic attrition and counseling. Fifth, academic achievement displayed moderate negative relationships with the frequency of academic and nonacademic counseling and these variables in turn displayed moderate positive relationships with washback as well as academic attrition and nonacademic attrition. Sixth, time in special instructional assistance appeared to represent a somewhat unique outcome variable in the sense that it was not strongly related to any outcome measure except academic counseling. Seventh, measures of the diversity of course materials, the reading difficulty of course materials, abstract knowledge requirements and predicted attrition rates were all highly intercorrelated, and tended to display a strong, albeit complex, pattern of relationships with the remaining course

content variables. Eighth, yearly flow and personnel requirements were highly correlated, and tended to be related to a number of other course content variables. Ninth, a variety of course content variables including day length, course length, instructor quality, feedback, student faculty ratio, abstract knowledge requirements and yearly flow produced positive and negative relationships on the order of .20 with both achievement test grades and SIA time.

Path Analysis Findings

Synthesis and evaluation of the foregoing correlational findings resulted in the hypothetical model presented schematically in figure one. This figure also displays the path coefficients produced by the Lisrel V analysis of this model. As may be seen in Figure 1, this model postulates a rather complex set of relationships among the various outcome variables. In accordance with the correlational data the model indicates that the assessed quality of student performance has a negative impact on the frequency of academic (-.20) and nonacademic counseling (-.23). Academic counseling is in turn held to effect academic attrition (.22) and washback (.34) while nonacademic counseling is held to level to nonacademic attrition (.24). Thus this model indicates that the assured quality of student performance does not directly impact attrition. Rather its effects are moderated by the decision humans make in counseling sessions. The positive causal paths from academic to nonacademic counseling (.15) and from washback to academic attrition (.25) were specified because academic counseling may occasionally reveal nonacademic problems and because washback is often a

direct precursor of academic attrition in the Air Force. Quality of performance had only a weak causal impact on SIA time (-.07), underscoring the role of SIA time as a remedial device, but as expected the problems revealed by SIA may lead to academic counseling (.18).

Within this model it is postulated that any impact student inputs have on counseling, attrition and washback are moderated by the assessed quality of a student's academic performance. Scores on the selector AIs (.16) and the Air Force reading ability test (.16) had the strongest effect on measured achievement. However, a sizable path coefficient was also produced by the measure of academic motivation (.14). These findings seem to confirm the ancient truism that intellectual ability and motivation are the prime determinants of training performance. Nevertheless, it should be recognized that educational level (.12) and age (.11) also had a significant impact on the assessed quality of performance. Apparently, both maturity and earlier success in adapting to an academic environment may contribute to training performance. Finally, it should be noted that specific educational preparation for an AFS produced the weakest effect observed among the student input variables; yielding a path coefficient of only .07 against the assessed quality of performance. This result may reflect the fact that in a well designed technical training program targeted at entry level personnel, training performance will not be greatly effected by prior experience.

Obviously, this model postulates a rather complex set of relationships among the course content variables, and between these variables and the assessed quality of performance and SIA time. Before examining the

relationship of the course content variable to performance in training, it would seem necessary to first examine the relationships among the various course content variables. Broadly speaking, this model postulates that the general characteristics of Air Force training programs are dictated by three primal variables; these being, 1) manpower requirements; 2) the learning difficulty of occupational tasks, and 3) the difficulty of program of instruction used to train these tasks. Thus in accordance with trainer comments the difficulty of the job, the difficulty of the training program and the number of bodies to be produced determine course parameters. Of course, subject matter difficulty and manpower requirements represent latent variables. As might be expected, manpower requirements were best defined by yearly flow. On the other hand, course diversity, predicted attrition rates, reading difficulty and abstract knowledge requirements all made comparable contributions to the definitions of subject matter difficulty although abstract knowledge requirements appeared to be of special significance. In examining the relationship among these three primal variables it was found that subject matter difficulty was positively related to occupational learning difficulty (.52), as might be expected given the careful design of Air Force training programs. Occupational difficulty was also positively related to manpower requirements (.38), perhaps due to higher turnover in more difficult and marketable specialty areas. However, manpower requirements was found to be negatively related to subject matter difficulty (-.23) reflecting the tendency of high flow courses to be less demanding and better defined.

Having defined these three primal variables and elaborated on their

interrelationships, it would now seem germane to examine the specific manner in which they determine the various course design parameters. For the sake of clarity these relationships are presented in Figure 1 such that the first arrow entering course length reflects the effects of subject matter difficulty, the second occupational difficulty and the third manpower requirements. As may be seen, subject matter difficulty (.56) and occupational difficulty (.46) had a direct impact on course length as is might be expected in a situation where individuals must be trained to a constant performance standard regardless of personnel needs. Day length however was positively influenced by manpower requirements (.36) and negatively influenced by subject matter difficulty (-.39). This pattern of relationships was in line with instructors' report that an eight hour classroom day was too much for students to handle in a difficult training program but that it served as one means for increasing flow. Instructor quality reflected behavioral checklist, evaluations of the effectiveness of the instruction provided in a program. Thus it was not surprising that with more students (-.47), more difficult tasks (-.30) on more difficult training materials (-.10) instructor effectiveness declines. While other examples of this sort might be cited, the foregoing discussion should serve to demonstrate that the three primal content variables determined course design parameters in an interpretable and highly cohesive fashion.

The impact of the course content parameters on the assessed quality of student performance and SIA time is reflected respectively in the two arrows following from each course parameter in Figure 1. Among the course parameters, feedback intensity (.09, .08), instructor quality (.05, .08) and

course length (.05, .08) were found to have the strongest impact on both quality of performance and SIA time. The remaining course parameters yielded trivial path coefficients. However, this result should not be taken as indicating that the design parameters are of no consequence. Rather it indicates that these variables have little effect on performance apart from the three primal variables in a well designed program of instruction. Among the primal course content variables it was found that increasing subject matter difficulty (-.08), increasing occupational difficulty (-.13) and increasing manpower requirements (-.10) tended to reduce student achievement. Increasing subject matter difficulty (.16) and increasing occupational difficulty (.06) lead to greater SIA time, reinforcing the hypothesis that it serves as a remedial device, while increasing manpower requirements (-.05) led to decrements in SIA time by limiting instructors investment in any given student.

Taken as a whole, the preceding discussion indicates that the model laid out in Figure 1 was associated with a highly meaningful pattern of path coefficients. However, before concluding this section two additional points bearing on the content of this model should be considered. First, inspection of the relationships among the error terms indicated that correlated error had little impact on the relationships observed among the student input, course content and training outcome variables. Second, although the relationships among the three primal content variables and the student input variables are not presented in Figure 1, this analysis did yield some interesting results. Here it was found that subject matter difficulty was positively related to all of the student input variables on the order of .30,

while manpower requirements were negatively related to all of the student input variables on the same order of magnitude. These relationships seem to reflect the indexing of entry requirements against the difficulty of training programs, and the fact that when personnel needs are high, the requisite number of individuals may be obtained only by accepting some lower quality trainees.

A somewhat better grasp of the overall productive power of this model might be obtained by considering the multiple Rs generated for each dependent or endogenous variable. These multiple Rs are presented in Table 3 for each of the training outcome variables and course parameters. The multiple Rs generated by the three primal variables against each course parameter lay between .54 and .86 indicating that subject matter difficulty, occupational difficulty and manpower requirements provide an excellent definition of course parameters. More importantly, the multiple Rs generated by the model against such of the outcome measures indicate that the model yielded excellent prediction of training performance. For instance, a multiple R of .75 was obtained against the assessed quality of student performance. Multiple R's of .60, .76 and .83 were obtained for nonacademic counseling, washback and nonacademic attrition while multiple R's of .50 and .57 were obtained for academic counseling and academic attrition. The multiple R obtained for SIA time was .35 indicating relatively weak prediction, perhaps due to its special role as a remedial device. The evidence pertaining to the effectiveness of this model provided by the multiple R's was confirmed by the goodness of fit test and residual time. The goodness of fit was .59 and the residual was .19. Both these figures indicate that the model laid out above

did indeed capture the relationships among the student input, course content and training outcome variables.

Course Validation Analyses

Having demonstrated that the model formulated in the present study was capable of predicting training outcomes and describing the technical training processes, the next question to be considered was whether the model was sufficiently stable and general to allow it to be employed in routine decision making at the AFS level. To address this issue a cross-validation study was conducted by determining the status of nine independent AFSs on the student input and course content variables, and then employing the regression equations provided by the model to generate standard score and raw score predicted outcomes. These predicted outcomes were then compared to the outcomes actually observed in each AFS.

The results obtained in this cross validation effort are presented in Table 4. As may be seen, there is generally close correspondence between the prediction generated by the model and the outcomes actually observed in each AFS. In no case did the average absolute difference between observed and predicted standard scores exceed half a standard deviation. The difference observed for the assessed quality of student performance was only one third of a standard deviation while the standard score difference observed for academic counseling, washback academic attrition, nonacademic counseling and nonacademic attrition lay near or below one quarter of a standard deviation. A somewhat larger average difference was observed for SIA time, as might be expected on the basis of the multiple R generated by

the model. It is also of note that although only one nonacademic attrition was contained in the cross validation sample, the model accurately predicted that this would occur among jet engine mechanics. Further, it appears that the predictive accuracy of the model held across AFSs, in the sense that it appeared to yield equally accurate predictions for AFSs in the general and administrative aptitude areas, such as computer programmer or financial services specialist, and AFSs, in the mechanical and electronics areas, such as navigation systems specialists and jet engine mechanics. Thus, the predictive accuracy of the model appears to generalize across AFSs, of differing content.

Discussion

Model Content

The results tried out in the foregoing section indicate that a stable, general model of substantial predictive power was formulated in the present study, and so it would seem appropriate to consider some of the practical and theoretical implications of this model. At a general conceptual level the content of this model has a number of important implications. For instance, the relative magnitude of the path coefficients associated with the student input and course content variables would tend to suggest that what the individual brings to the learning activities is of somewhat greater import to performance than what is done to the individual in training. This conclusion is in line with Tyler's (1964) comment that student abilities are likely to have more impact on educational attainment than educational content per se. Nevertheless, these statements are not

intended to imply that course content is irrelevant to understanding and predicting training performance. Clearly, the primal course content variables and aspects of the instructional system, such as course length, feedback and instructor quality, may have a substantial impact on training performance. When this observation is coupled with the fact that some systematic and meaningful relationships exist between the primal course content and student input variables, it indicates that fully adequate predictions of training performance can be obtained only by recognizing the complex multivariate nature of training, and carefully considering both student inputs and course content in designing predictive systems.

Beyond recognizing the complex nature of the relevant predictors, the model suggests that somewhat greater caution should be exercised in making statements concerning the relationships between training outcomes and student inputs or course content. The model formulated in the present study indicates that inputs and course content may effect learning as indexed by achievement test performance. However, learning, student inputs and course content are not directly related to more distal indices of performance such as attrition or washback. Rather, the effects of inputs, course content and learning on these outcomes is moderated by trainers counseling discussions. This implies that trainers exercise a high degree of control over training outcomes, and that a point-to-point correspondence between aptitude or course length and attrition can not be assumed. Moreover, prediction of these outcomes is likely to be poor unless trainers decisions are considered.

Aside from these issues bearing on performance prediction, the model has

some interesting implications for our conceptions of training systems. The results obtained in the present study indicate that certain primal variables, such as the difficulty of the tasks to be trained, the difficulty of training materials and the number of individuals to be trained, drive the design of training programs. By the identification of primal variables of this sort and specification of their relationship to student inputs and course parameters, it might be feasible to empirically identify optimal course parameters. Thus it should be possible to employ this model to provide a more scientific framework for instructional systems design rather than relying on the current art of trial and error.

Model Applications

Of course, the model formulated in this study was constructed with a particular practical purpose in mind, that is to provide personnel managers with a systematic basis for predicting the impact of changes in student inputs, such as aptitude, on training performance, and to provide a framework for adjusting course content in relation to changes in student inputs. Essentially, the model formulated in this present study would be used as a simulation device to accomplish this. Here anticipated changes would be used to replace current mean values for the student input and course content variables. Subsequently, the predictions provided by the model would be used to predict the average outcomes likely to be observed in an AFS under these conditions. On the basis of certain preliminary work, it also appears that the outcomes included in this model can be costed through a variation on the Air Forces current accounting system, thus allowing the cost impact of these

simulated changes to be assessed.

It is anticipated that this simulation capability will be used in a variety of decision making situations. Simulated changes in student inputs and the resulting change in training outcomes might be employed as a guide in determining ascension policy. For instance, anticipated changes in aptitude requirements or educational requirements might be introduced into the model to generate simulated outcomes. The nature and costs of these outcomes relative to the existing outcomes and costs in an AFS might then be used to determine the appropriateness of these entry requirements. Further, this model might be used as a basis for predicting the effects of changes in the characteristics of the applicant population on training performance. Anticipated shifts in the mean aptitude, age or educational level of the recruit pool would simply be entered into the equations provided by the model to determine the likely change in training performance. Finally, as was mentioned earlier, the model might be employed as a framework for course design. In this instance, the status of the AFS on the primal course content variables would be assessed, and used to predict the requisite course length and student faculty ratios on the basis of historic relationships. Moreover, anticipated changes in course parameters might be entered into the model equations and used to predict their effects on training outcomes, and offset any negative impacts of changing student inputs. Thus the model might provide the trainer with better control over design changes, and a vehicle from relating design changes to changing student inputs.

To this point the discussion has considered only a few of the more

tangible applications of this modeling effort. However, it appears modeling efforts of the sort carried out in the present study have a critical but rather nebulous application which is worthy of mention. Quite often in formulating personnel policy managers are asked to make decisions that might have a variety of potential effects without a clear idea of exactly what factors should be considered in the decision making process or exactly how these factors are likely to interact in determining outcomes. One important benefit of this effort is that it served to systematically and empirically define the significant variables influencing training outcomes in the Air Force. Hopefully, by enhancing managers understanding of the relevant variables this model will provide a basis for better informed policy decisions.

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REFINED MODEL WITH STANDARDIZED PATH COEFFICIENTS

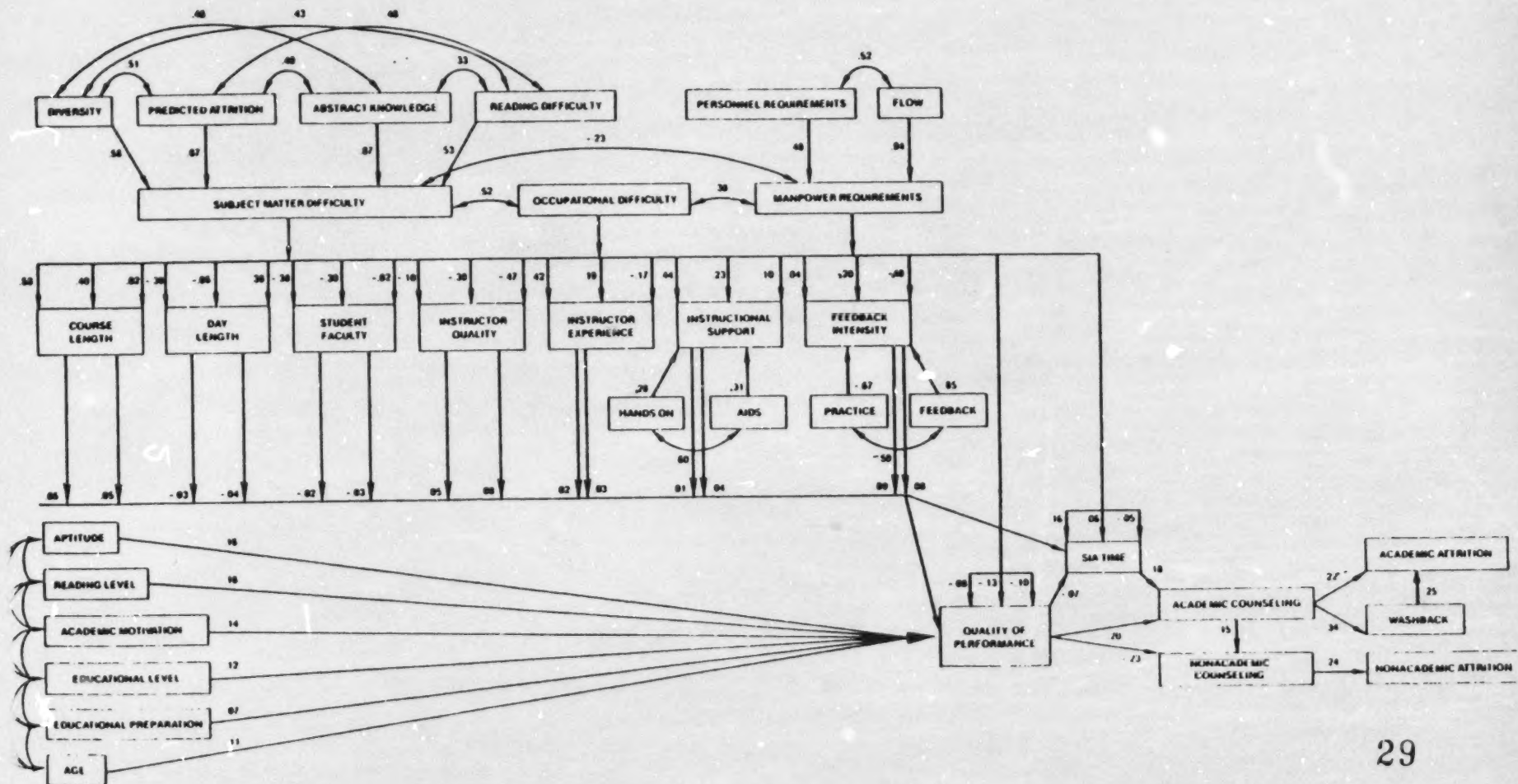


TABLE ONE

SUMMARY OF VARIABLES AND MEASURES

<u>OUTCOME VARIABLES</u>	<u>MEASURE</u>	<u>SOURCE</u>
Quality of Student Performance	Average of end of block tests	ATC 156
SIA Time	Time in special instructional assistance	ATC 156
Academic Counseling	Number of academic counseling sessions	ATC 156
Non-academic Counseling	Number of non-academic counseling sessions	ATC 156
Washback	Number of hours of retraining	ATC 156
Academic Attrition	Elimination for academic reasons	ATC 156
Non-academic Attrition	Elimination for non-academic reasons	ATC 156
 <u>STUDENT INPUTS</u>		
Aptitude	Scores on Relevant Selector AI	PACE
Reading Level	Total scores on the AFRAT	ATC 156
Academic Motivation	Number of difficult courses taken	PACE
Simple Interest	Received GTEP preference	PACE
Preference Interest	Received preferred specialty	PACE
Educational Level	Highest educational level	PACE
Educational Preparation	Recommended prerequisites taken	PACE
Age	Years from birth	PACE

TABLE ONE (CONTINUED)

SUMMARY OF VARIABLES AND MEASURES

<u>COURSE CONTENT VARIABLES</u>	<u>MEASURE</u>	<u>SOURCE</u>
Course Length	Number of total instructional hours	POI
Day Length	Length of academic training day	POI
Student-Faculty Ratio	Number of students per teacher	TP
Instructor Quality	Average quality of instructor performance evaluations	Course Supervisors
Instructor Experience	Average months of instructor experience	~~POI~~ COURSE SUPERVISORS
Aids in Use	Number of instructional aids divided by course length	POI
Hands-on Instruction	Hours of hands-on instruction divided by course length	POI
Amount of Feedback	Number of evaluations divided by course length	POI
Amount of Practice	Course length divided by number of units	POI
Reenlistment Bonus	Availability of a selective reenlistment bonus	AFHRL
Yearly Flow	Number of students to be trained yearly	TP
Occupational Difficulty	Overall learning difficulty of occupational tasks	AFHRL
Reading Difficulty	Reading grade level of course materials	ARRO Staff
Abstract Knowledge	Ratings of abstract knowledge requirements	ARRO Staff
Diversity	Number of units	POI
Predicted Attrition	Administrative attrition rate	TP

TABLE TWO

MEANS AND STANDARD DEVIATION OF VARIABLES

	FULL SAMPLE		DEVELOPMENT SAMPLE		CROSS VALIDATION SAMPLE	
	$\bar{X}$	SD	$\bar{X}$	SD	$\bar{X}$	SD
<u>STUDENT INPUTS</u>						
Aptitude (Selector AI)	69.80	16.30	68.00	16.20	73.20	15.90
Mechanical	55.10	22.40	54.40	22.30	59.30	22.60
Administrative	63.20	19.50	62.70	19.50	65.80	19.70
General	65.30	16.90	64.70	16.80	68.60	17.30
Electronics	63.50	18.50	62.70	18.50	67.80	18.00
Reading Level	11.40	1.00	11.40	1.00	11.60	1.00
Academic Motivation	39.00	13.40	38.40	13.30	42.00	13.50
Simple Interest	1.40	.49	1.40	.49	1.50	.50
Preference Interest	4.40	.86	4.40	.87	4.50	.82
Educational Level	2.10	.45	2.10	.42	2.20	.56
Educational Preparation	1.60	.94	1.60	.87	1.90	1.10
Age	20.10	2.20	20.00	2.10	20.50	2.30
<u>COURSE CONTENT</u>						
Course Length	413.90	309.30	386.30	302.20	569.90	297.70
Day Length	.48	.49	.46	.49	.62	.48
Student-Faculty Ratio	9.10	4.80	9.20	4.90	8.30	3.90
Instructor Experience	32.50	14.70	29.70	12.90	49.60	13.60
Instructor Quality	2.50	.16	2.50	.16	2.40	.13
Aids In Use	.27	.10	.27	.10	.28	.13
Hands-on Instruction	.41	.13	.41	.13	.37	.10
Amount of Feedback	.34	.12	.35	.13	.28	.06
Amount of Practice	8.50	3.10	8.60	3.00	8.00	3.80
Reenlistment Bonus	.44	.49	.42	.49	.61	.48
Yearly Flow	1943.60	2662.50	2204.90	2782.00	324.50	118.00
Occupational Difficulty	97.50	22.10	93.40	18.80	125.20	23.30
Reading Difficulty	10.90	.63	11.00	.67	10.90	.30
Abstract Knowledge	2.40	.98	2.20	.91	3.20	.93
Predicted Attrition	.09	.03	.09	.03	.13	.02
Diversity	54.80	43.30	49.90	41.10	45.40	45.20

TABLE TWO (CONTINUED)

MEANS AND STANDARD DEVIATION OF VARIABLES

	FULL SAMPLE		DEVELOPMENT SAMPLE		CROSS VALIDATION SAMPLE	
	$\bar{X}$	SD	$\bar{X}$	SD	$\bar{X}$	SD
<u>OUTCOME VARIABLES</u>						
Quality of Student						
Performance	85.20	7.60	85.000	7.70	86.800	6.90
SIA Time	6.50	15.40	5.900	15.20	10.200	15.80
Academic Counseling	1.40	3.40	1.400	3.40	1.600	3.40
Non-academic Counseling	.17	1.50	.190	1.60	.080	.86
Washback	11.10	51.50	8.800	42.70	24.400	84.50
Academic Attrition	.02	.16	.020	.15	.050	.22
Non-academic Attrition	.004	.06	.004	.06	.011	.03

TABLE THREE

MULTIPLE R's AND R^2 FOR TRAINING OUTCOMES AND COURSE PARAMETERS

	R	R^2
Assesed Quality of Performance	.75	.54
SIA Time	.35	.12
Academic Counseling	.60	.36
Non-academic Counseling	.50	.25
Washback Time	.76	.59
Academic Attrition	.83	.70
Non-academic Attrition	.59	.35
Course Length	.86	.75
Day Length	.60	.36
Student-Faculty Ratio	.62	.38
Instructor Quality	.58	.34
Instructor Experience	.60	.36
Instructional Support	.54	.30
Feedback Intensity	.68	.47

TABLE FOUR

Cross Validation Results Contrasting
Predicted and Observed Outcomes

Title	Speciality Code	Assessed Quality of Performance				SIA Time				Academic Counseling			
		Raw Scores		Standard Scores		Raw Scores		Standard Scores		Raw Scores		Standard Scores	
		OBS	PRED	OBS	PRED	OBS	PRED	OBS	PRED	OBS	PRED	OBS	PRED
Aircraft Electrical Systems Specialist	42330	90.0	86.5	.64	.16	3.8	10.8	-.13	.32	2.3	1.5	.26	.04
Jet Engine Mechanic	42652	85.0	81.5	.00	-.45	4.6	10.7	-.08	.32	.7	1.4	-.20	.01
Financial Management Specialist	67231	86.4	88.2	.19	.41	10.3	5.9	.28	.00	1.3	1.2	-.03	-.07
Medical Laboratory Specialist	92430	84.9	89.5	.90	.59	26.4	10.1	1.21	.28	2.5	1.2	.32	-.05
Armament Systems Specialist	46230	85.9	85.3	.11	.05	1.5	8.1	-.28	.15	.8	1.5	-.15	.03
Ground Radio Operator	29333	86.6	86.6	.20	.20	12.5	6.0	.43	.01	2.8	1.3	.24	.29
Aircraft Warning Radar Specialist	30332	89.5	88.3	.58	.43	13.1	10.9	.32	.48	2.1	1.5	.20	.20
Navigation Systems Specialist	32831	90.5	88.1	.74	.39	3.3	10.6	-.17	.33	1.4	1.4	.00	.00
Computer Programming Specialist	51131	87.4	90.4	.37	.71	5.8	10.0	-.01	.27	.6	1.1	-.23	-.07
		2.34		.331		6.83		.421		.67		.182	
Title	Speciality Code	Nonacademic Counseling				Washback Time				Academic Attrition			
		Raw Scores		Standard Scores		Raw Scores		Standard Scores		Raw Scores		Standard Scores	
		OBS	PRED	OBS	PRED	OBS	PRED	OBS	PRED	OBS	PRED	OBS	PRED
Aircraft Electrical Systems Specialist	42330	.10	.13	-.06	-.03	8.8	9.3	.00	.01	.02	.02	.00	.013
Jet Engine Mechanic	42652	.16	.26	-.01	.08	16.5	10.5	.18	.04	.03	.02	.06	.011
Financial Management Specialist	67231	.05	.05	-.09	-.09	25.0	7.7	.37	-.02	.06	.02	.26	-.014
Medical Laboratory Specialist	92430	.11	.00	-.05	-.12	53.7	8.0	1.00	-.02	.11	.01	.50	-.017
Armament Systems Specialist	46230	.07	.14	-.08	-.01	14.9	9.3	.14	.01	.05	.02	.20	.010
Ground Radio Operator	29333	.03	.10	-.10	-.05	28.0	8.3	.44	-.01	.06	.02	.26	-.011
Aircraft Warning Radar Specialist	30332	.06	.06	-.08	-.08	13.9	9.1	.11	.01	.04	.02	.13	.015
Navigation Systems Specialist	32831	.05	.08	-.09	-.07	14.0	9.0	.12	.01	.01	.02	-.06	.003
Computer Programming Specialist	51131	.02	.00	-.10	-.14	9.2	7.7	.02	-.02	.00	.02	-.12	-.024
		.64		.05		11.62		.27		.028		.172	
Title	Speciality Code	Nonacademic Attrition											
		Raw Scores		Standard Scores									
		OBS	PRED	OBS	PRED								
Aircraft Electrical Systems Specialist	42330	.000	.003	-.07	-.021								
Jet Engine Mechanic	42652	.010	.006	.10	.069								
Financial Management Specialist	67231	.000	.002	-.07	-.023								
Armament Systems Specialist	92430	.000	.002	-.07	-.032								
Ground Radio Operator	46230	.000	.003	-.07	-.001								
Aircraft Systems Specialist	29333	.000	.003	-.07	-.012								
Ground Radio Operator	30332	.000	.002	-.07	-.022								
Aircraft Warning Radar Specialist	32831	.000	.002	-.07	-.014								
Navigation Systems Specialist	51131	.000	.001	-.07	-.037								
		.002		.031									

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